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MindBridge: A Transformer-Based Conversational Agent for Real-Time Depression and Anxiety Detection and Support in University Students

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Abstract

Mental health challenges are becoming a major concern among university students who still have limited access to appropriate and affordable support due to barriers such as stigma, cost, and time limitations. Most of the digital tools available, such as Wysa and Woebot, are based on rigid rule-based logic and are incapable of understanding the contextual nuances of student-expressed emotional distress. For this system, a system-oriented, agile research methodology was used. Three public datasets the Mental Health Text Classification Dataset, the Reddit Depression Dataset, and the EmpatheticDialogues Dataset, were combined and balanced to create a training corpus of 24,000 labeled entries equally distributed across three emotional categories: depressive, anxious, and neutral. The Mental-BERT transformer model was trained on this corpus in five epochs with the help of Google Colab's GPU infrastructure. This classification model was then incorporated into a Flask web backend, together with the Groq API for conversational response generation, a PostgreSQL relational database for secure data persistence, and a web-based frontend consisting of a responsive chat interface with user authentication. After evaluating the fine-tuned Mental-BERT model on a test set of 3,600 samples that were not used during training, the overall classification accuracy was 96%. Also, the macro-averaged precision, recall, and F1-score were equally high at 96% across the three classes. We carried out a user study with 58 university students who gave a mean System Usability Scale score of 76.55 for MindBridge. That score belongs to the good usability category and is also above the industry average threshold of 68. More than 70% of participants graded the system as Good or Excellent. Empathy and conversational quality metrics showed that the respondents considered MindBridge a source of empathy and assistance, while the mean figure for perceived usefulness was 4.03 out of 5. All 16 automated system tests were successfully passed. Results show that using a domain-specific pre-trained transformer model alongside prompt-engineered large language model response generation and a hybrid safety architecture can lead to the development of a very accurate, usable, and empathetic mental health support system for university students.

Keywords: MindBridge, Transformer, Conversational Agent, Depression, Anxiety, Detection, Mental-BERT Model, Mental Health, Emotional Classification.

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INTRODUCTION

Technology has transitioned from just a tool we use to the very fabric of our daily existence, and as part of these technological advancements, AI has contributed to health care in innovative ways that were previously unattainable (Lata & Singh, 2025). These new technological innovations are not just for physical health, but they have also extended into mental health. Mental health is an individual's state of mind that allows them to function properly in their daily activities by coping with the stresses of life, learning well, working well, and contributing to their community (World Health Organization, 2023). Mental health issues have become very rampant, and a niche group of people who constantly battle with it are students. Due to the various issues that accompany traditional mental health support systems, such as time constraints, stigmas, anxiety about physical sessions, high cost of therapy, and so on, students prefer AI applications and chatbots (Ahad et al., 2023).

Mental health conditions are worldwide, but many remain undiagnosed and untreated due to stigma, limited access to mental health services, and a lack of awareness about symptoms and treatment options (Vasim et al., 2025). While mental health education has increased, most traditional mental health services often come with excessive costs, geographical limitations, and scheduling constraints that prevent timely intervention (Wang et al., 2024). Digital alternatives have emerged to bridge these gaps, but they frequently fail to provide effective support due to a fundamental technical gap in their AI architectures.

Most existing mental health chatbots, such as Woebot and Wysa, were built around rigid decision trees or static CBT script logic; even as some of these platforms pilot large language model components for broader conversational range, their core safety and crisis-handling logic remains rule-based, which limits their ability to detect clinical leaks which are the subtle linguistic and context switches that signal a transition from routine stress to an acute depressive crisis. These systems also suffer from poor contextual persistence, because they lose the thread of a user's history over long-term interactions, leading to generic and repetitive responses that can alienate users during vulnerable moments. Current platforms also lack specialization tailored to the unique stressors of a student population, such as academic burnout, identity struggles, and social isolation. When presented with current digital alternatives for mental health support, they fail to address ethical concerns on how the user's data is handled, the bias of the system, and how crises are managed (Hoose & Králiková, 2024). Unlike these closed, general-purpose platforms, MindBridge is built around a transformer model pre-trained specifically on mental health text (Mental-BERT) and an openly documented architecture, which the present study argues gives it a domain-specific and architecturally transparent advantage over proprietary, general-purpose competitors.

NLP is a branch of AI that allows computers to understand and manipulate human language (Khurana et al., 2023). In mental health, AI applications and chatbots are being used to provide support to individuals with mental health issues, and NLP is what allows these chatbots and virtual assistants to engage in meaningful conversations with their users. This technology allows for these applications to identify patterns of emotional distress in text and voice data, showing promise when it comes to early detection of mental health issues. This project introduces MindBridge, an AI-based conversational mental health support system specifically for students. By leveraging advanced Natural Language Processing (NLP) for data-driven insights and personalized intervention logic, this system offers a stigma-free, affordable, and high-fidelity virtual companionship that adapts to the specific needs of the student experience. The system combines deep learning-based emotional classification, large language model response generation, and a deterministic crisis detection mechanism.

RELATED WORKS

Historical Background and Early Approaches

Mental health care has evolved significantly over time, growing with psychology and technology to provide better care. Treatment of mental illness using traditional methods such as institutions and psychotherapy was the primary focus in the late 19th and early 20th centuries, before the second half of the 20th century brought about self-help, outpatient, and community support that extended the boundaries of mental health care services. Mental health care in the 1980s and 1990s began to be transformed by digital health technology, with basic computerized CBT programs forming the basis for the use of technology in the provision of mental health support outside of the clinical setting.

In recent years, mobile devices can now make use of generative AI to enhance the performance of tasks (Na & Lee, 2024), giving rise to more complex mental health applications that could track symptoms, suggest coping mechanisms, and so much more. Study has also shown that the majority of such mobile applications are effective in managing anxiety and depression (Moulaei et al., 2023). The development of the sector from being within institutions to being delivered through applications justifies the need for a unique mental health web application that is easy and convenient to use, and these issues align with the goals of this system.

NLP Algorithms for Depression and Anxiety Detection: Traditional Machine Learning vs Deep Learning

Alsagri & Ykhlef (2020) described a system for detecting depression and anxiety by analyzing Twitter data using classical machine learning classifiers, including Support Vector Machines (SVM), Naive Bayes, and Random Forest. SVM achieved the highest accuracy among the classifiers tested, demonstrating that conventional machine learning methods could effectively distinguish between depressed and non-depressed users when linguistic features were well engineered. However, this approach relies entirely on manually engineered features, which limits its ability to capture contextual meaning, sarcasm, or the subtle linguistic shifts that characterize depression and anxiety.

Bokolo & Liu (2023) performed a thorough comparison between traditional machine learning and deep learning methods for depression and anxiety detection using a dataset of 632,000 tweets. They evaluated transformer-based models, including DistilBERT, DeBERTa, and RoBERTa, alongside classic classifiers. RoBERTa achieved 98.1% accuracy, significantly outperforming the traditional classifiers, with the researchers attributing this performance gap to transformer models' superior contextual understanding and richer semantic representation.

These studies establish a clear progression from conventional machine learning relying on hand-crafted features towards deep learning models capable of automatically deriving contextual and sequential patterns from raw text. Transformer-based architectures such as BERT consistently outperform traditional classifiers across benchmarks, and this evidence directly informs the decision to implement a deep learning pipeline for depression and anxiety identification in the proposed system.

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Related Works on Digital Mental Health Interventions

Appleton et al. (2021) conducted a systematic review analyzing telemental health services during the COVID-19 pandemic, finding that teletherapy increased accessibility, particularly for students and young adults. However, the study did not examine AI-driven systems for automated emotional analysis or early depression and anxiety detection. Wani et al. (2024) conducted a scoping review of digital interventions in low- and middle-income countries, finding that mobile apps were both feasible and effective in improving adolescent mental health. This study highlights the importance of accessibility and inclusivity when designing student mental health apps in developing regions like Nigeria but leaves a gap regarding the high-pressure academic environment specific to university students.

Lattie et al. (2022) assessed IntelliCare, a self-guided mental health app for college students, with results showing significant reductions in stress and improved coping behaviors, though it leaves a gap regarding stigma reduction and cultural barriers. Cruz-Gonzalez et al. (2025) concluded that AI enhances personalization and accessibility in mental health care but raises ethical concerns about data handling while leaving a gap regarding human-centered integration into daily student routines. Amanvermez et al. (2022) revealed that self-guided stress management interventions improved coping skills and emotional regulation among college students, but without examining AI-powered systems for real-time emotional analysis or early detection of depression and anxiety.

These studies confirm that self-help digital tools can be a great source of support for college students. Nonetheless, the majority of existing work concentrates on clinical treatment rather than preventative care for typical academic stressors, and there remains a need for student-oriented, ethically grounded, and adaptive AI systems that detect early signs of emotional distress in a stigma-sensitive manner.

Strengths and Weaknesses of Existing Mental Health Support Systems

Meditation and mindfulness apps such as Headspace and Calm provide guided meditation, breathing exercises, and relaxation programs, with accessibility and simplicity as their biggest advantages. Nevertheless, both applications lack personalized clinical support of any kind, with no functionality for distress detection, no pathway for escalation of users in crisis, and no conversational interface capable of engaging with the user's lived experience.

Woebot and Wysa are two mental health conversational agents that operate based on CBT principles, offering 24/7 availability and a stigma-free space for users to share their emotional difficulties. Both were originally built on static, rule-based conversational logic and keyword-triggered reply pathways, and while Wysa has since begun piloting LLM-based components and Woebot experimented with generative-AI-assisted responses before its consumer app was discontinued in 2025, both platforms remain closed, general-purpose systems that retain rule-based logic for safety-critical content rather than a model trained end-to-end on mental health language. This architectural choice implies that their answers still lean on surface-level pattern matching for a large share of interactions rather than the kind of deep, domain-specific contextual understanding MindBridge is designed around, causing them to generate generic or unhelpful responses when users express distress indirectly or ambiguously. By contrast, MindBridge's Mental-BERT classifier is trained specifically on mental health text and its full pipeline is openly documented in this paper, giving it a domain-specific and architecturally transparent advantage over these proprietary platforms. BetterHelp facilitates direct communication with licensed therapists, but the high cost of subscription makes it almost impossible for university students on a tight budget to afford.

Across all categories reviewed, existing platforms either offer rich content without contextual intelligence or conversational interaction without genuine language understanding. These limitations directly motivate the adoption of a deep learning approach in the proposed system, as transformer-based models are capable of understanding contextual nuance and subtle shifts in expression that rule-based systems invariably miss.

Research Gaps Addressed by This Study

The literature demonstrates that digital mental health platforms have significantly enhanced accessibility, engagement, and stress management among students, yet existing studies reveal critical gaps. These include a lack of real-time emotional analysis, limited focus on early detection of depression and anxiety, insufficient attention to preventative strategies for non-clinical stressors, inadequate personalization to the specific needs of university students, and unresolved ethical concerns on how user data is handled and how crises are managed (Hoose & Králiková, 2024).

The proposed system, MindBridge, seeks to address these gaps by providing a personalized and accessible platform that combines real-time emotional analysis, early detection of depressive symptoms, and preventative mental health support, aimed specifically at students navigating academic pressures and social challenges.

METHODOLOGY AND SYSTEM DESIGN

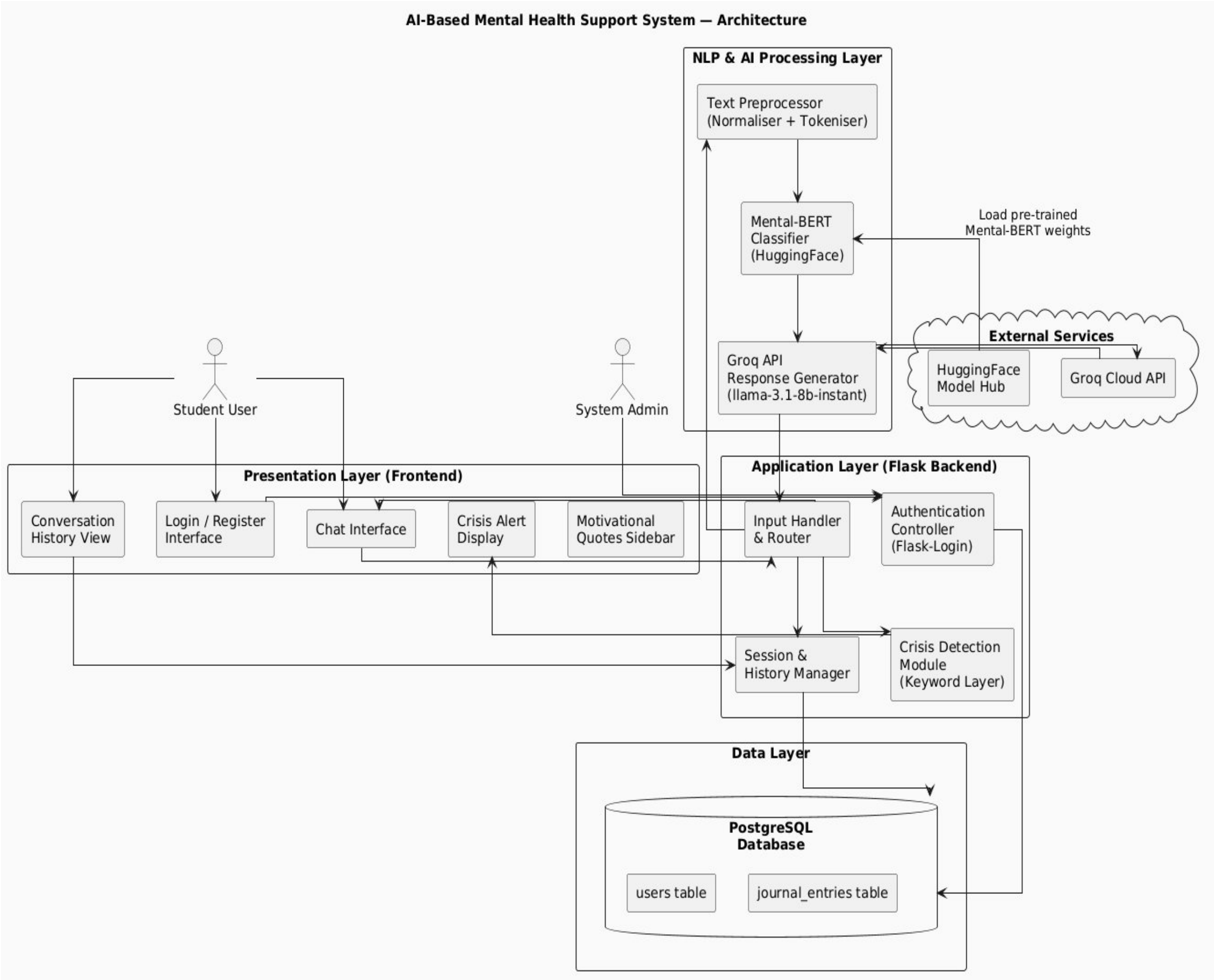
Research Design

This study adopts a system-oriented and model-driven research design because it focuses on the development and evaluation of an intelligent software system rather than purely behavioral analysis. The research approach is primarily quantitative, as it involves training and evaluating a deep learning model on labeled textual data using measurable metrics such as classification accuracy, F1-score, precision, and recall. The research proceeds through four logical phases: requirements analysis and technology selection, deep learning model evaluation and selection, full-stack system implementation, and evaluation through both quantitative and qualitative methods.

The Agile methodology is employed in the system's development, which aligns seamlessly with a system-oriented approach. Each sprint encompasses data preprocessing, model fine-tuning, and interface testing, allowing for rapid identification and correction of issues at each stage of development. Model-driven development is used to structure the deep learning components of the system, ensuring that theoretical foundations from NLP and mental health research are translated into practical and clinically meaningful system functionality.

System Architecture

MindBridge implements a full-stack web architecture consisting of three distinct functional layers: a React-based frontend, a Flask backend, and a PostgreSQL database. The Flask backend handles user requests, routes conversational inputs through the NLP pipeline, and returns classification outputs and recommendations to the frontend in real time. The Groq API is integrated into the backend for conversational response generation, and the complete system is connected through a RESTful interface. The system architecture is presented below:



Mindbridge Technology Stack

Layer	Technology	Purpose
Backend	Python 3.9+	Backend logic and model inference
Backend	PyTorch	Deep learning framework for model training and inference
ML	Hugging Face Transformers	Loading and fine-tuning Mental-BERT
Backend	Flask	Lightweight web framework for handling requests and routing
Database	PostgreSQL	Data persistence via SQLAlchemy and psycopg2
Frontend	HTML, CSS, JavaScript	Responsive frontend interface

Deep Learning Model

MindBridge uses two complementary AI components. The classification model is a fine-tuned instance of Mental-BERT, a BERT model pre-trained on a large corpus of mental health-related text from sources such as PubMed articles, clinical notes, and Reddit mental health communities. Mental-BERT was selected over the standard BERT-base model because its pre-training domain is directly aligned with the task of depression detection, reducing the amount of fine-tuning required and improving classification performance on in-domain text. The model is fine-tuned on the combined training corpus using a three-class classification scheme: depressive, anxious/stressed, and neutral.

The architecture of the fine-tuned model consists of an input layer that accepts tokenized sequences of up to 512 tokens using the BERT WordPiece tokenizer, a 12-layer transformer encoder stack applying multi-head self-attention across the full input sequence, and a fully connected classification head appended to the [CLS] token output that projects the 768-dimensional contextual representation into a 3-class probability distribution using softmax activation. Training was conducted using the AdamW optimizer with a learning rate of 2e-5, a batch size of 16, and a maximum of 5 training epochs, with early stopping based on the validation F1-score.

The response generation component uses the Groq API, which provides access to the llama-3.1-8b-instant large language model. Since Mental-BERT is an encoder-only model incapable of generating text, all conversational response generation is handled entirely through the Groq model. Four distinct system prompts were created for each input type: depressive, anxious, neutral, and crisis. Each prompt instructs the model to respond empathetically, incorporate coping strategy recommendations naturally, and end with an open-ended question to sustain the conversation. Response length was limited to 150 tokens to keep interactions clear and conversational.

Datasets

The datasets used in this study were obtained from established, publicly available mental health repositories. The use of pre-existing, ethically approved datasets eliminates the need to collect new sensitive data from real student participants during the development phase and ensures compliance with ethical guidelines governing mental health research.

Three datasets were used. The Mental Health Text Classification Dataset was obtained from Kaggle and contains 49,612 labeled text entries spanning four mental health categories: depression, anxiety, suicidal, and normal, drawn from online mental health communities and reflecting natural, user-generated expressions of emotional distress. The Reddit Depression Dataset was also obtained from Kaggle and contains 7,731 cleaned and labeled posts from the r/depression subreddit, labeled as depressive or non-depressive and representing informal written expressions of emotional distress that closely mirror how students communicate on digital platforms. The EmpatheticDialogues Dataset, developed by Facebook AI (Rashkin et al., 2019), consists of approximately 25,000 conversational exchanges grounded in 32 distinct emotional states, included to improve the model's exposure to empathetic conversational language patterns.

For the purpose of the classification task, the combined corpus of 121,934 samples was consolidated into three categories: depressive/high-risk (~38%), anxious/stressed (~32%), and neutral/emotionally stable (~30%). The dataset was split into training (70%), validation

(15%), and test (15%) subsets using stratified sampling to preserve class distribution and reduce the risk of class-imbalance bias in the final model.

Preprocessing Pipeline

Pre-processing is the first stage of the NLP pipeline and focuses on cleaning and standardizing user input before it is passed to the BERT tokenizer. Text normalization is applied to handle special characters, encoding artifacts, and inconsistent whitespace, and URLs, usernames, and non-textual symbols are removed to reduce noise. The cleaned text is then passed to the BERT WordPiece tokenizer, which inserts the [CLS] and [SEP] tokens, produces attention masks, and handles sequences through truncation at 512 tokens and padding for shorter sequences.

Notably, traditional preprocessing steps such as stop-word removal and lemmatization are intentionally omitted. These techniques strip contextual information that BERT's self-attention mechanism relies on to model meaning. Stop words such as "not" and "never" carry critical negation cues in depression detection, and their removal would degrade classification performance.

Evaluation

The model's performance was evaluated on a held-out test set of 3,600 samples using standard classification metrics. Accuracy measures the proportion of correctly classified samples out of the total test set. Precision measures the proportion of predicted depressive cases that are truly depressive, while recall measures the proportion of actual depressive cases that the model correctly identifies. In a clinical context, high recall for the depressive class is prioritized to minimize false negatives, which carry a greater risk than false positives. The F1-score, computed as the harmonic mean of precision and recall, is reported in both macro and weighted forms to provide a complete performance picture. A confusion matrix summarizing the distribution of true and predicted class labels across all three categories is also reported.

System usability was evaluated through a user study with 58 university students using the System Usability Scale (SUS), with additional qualitative measures covering empathy, perceived usefulness, and conversational quality. A suite of 16 automated system tests was also executed to validate end-to-end pipeline reliability.

RESULTS

Classification Performance on Test Set

The saved model from epoch 4 was evaluated on the held-out test set of 3,600 samples, achieving an overall accuracy of 96%. The full classification report is presented below

Classification Report on Test Set

Class	Precision	Recall	F1-Score	Support
Depressive	95%	94%	95%	1,200
Anxious	95%	97%	96%	1,200
Neutral	96%	95%	96%	1,200

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Class	Precision	Recall	F1-Score	Support
Macro Average	96%	96%	96%	3,600

The anxious class achieved the highest recall at 97%, meaning the model correctly identified 97% of all genuinely anxious inputs. The depressive class achieved the lowest recall at 94%, which is consistent with the observation that depressive and anxious language patterns frequently overlap, making some depressive inputs more likely to be misclassified as anxious than the reverse.

Automated Test Results

All sixteen pytest tests passed on the final build of the system with a total execution time of approximately 42 seconds, confirming that each functional component of the system behaves correctly.

Automated Test Results

Test Category	Tests Written	Tests Passed	Tests Failed
Crisis Detection	4	4	0
Classification	5	5	0
Authentication	3	3	0
API Endpoints	4	4	0
Total	16	16	0

User Study Results

A user study was carried out with 58 university students from various courses and academic levels, who were asked to interact with MindBridge and complete an evaluation survey. The survey consisted of the System Usability Scale (SUS) for measuring overall usability, and five additional questions assessing empathy and conversational quality using a 5-point Likert scale.

MindBridge achieved a mean SUS score of 76.55, placing it in the good usability category and above the industry average threshold of 68 (Brooke, 1996). Over 70% of participants rated the system as Good or Excellent, with 53.4% achieving an Excellent rating. The median score of 80.00 further confirms that the majority of users found MindBridge easy and comfortable to use.

SUS Score Distribution

Grade	Score Range	Number of Participants	Percentage
Excellent	≥ 80.0	31	53.4%
Good	68.0 – < 80.0	10	17.3%
Average	51.0 – < 68.0	12	20.7%
Poor	< 51.0	5	8.6%

The empathy and conversational quality ratings are presented in Table 4.4. The highest rated dimension was perceived usefulness for university students dealing with stress or anxiety (4.03/5), while the naturalness of responses scored 3.52/5.

Empathy and Conversational Quality Ratings

Question	Mean Rating
MindBridge responded in a way that felt empathetic and understanding	3.98 / 5
The responses felt natural and conversational, not robotic	3.52 / 5
I felt comfortable sharing how I was feeling with MindBridge	3.69 / 5
I think MindBridge could be useful for university students dealing with stress or anxiety	4.03 / 5

DISCUSSION OF FINDINGS

The evaluation results show that MindBridge delivers accurate emotional classification, safe crisis handling, and practically useful conversational support for university students without requiring additional domain-specific data beyond the three publicly available datasets used for training. The high macro-averaged F1-score of 96% across all three classes demonstrates that the system successfully distinguishes between depressive, anxious, and neutral language patterns, confirming that domain-specific pre-training is the primary driver of classification quality in mental health text analysis tasks.

The recall and precision scores show expected results for a Mental-BERT model fine-tuned in a three-class transfer environment. The slightly lower recall of 94% on the depressive class does not indicate low-quality output but instead reflects the established linguistic overlap between depressive and anxious language, where phrases such as "I cannot cope anymore" carry meaning that is genuinely ambiguous between the two categories. This is consistent with findings in the wider mental health NLP literature rather than a fundamental model limitation.

The design choice to use a hybrid classification and response generation architecture proved to be an essential element of the system. Early prototypes that displayed raw classification labels and confidence scores alongside responses produced a clinical and diagnostic tone that undermined the supportive intent of the system. Replacing these visible outputs with naturally embedded coping strategy suggestions removed this failure mode while preserving the underlying classification capability, which showed its best performance when combined with the Groq API's conversational generation abilities.

MindBridge achieves usability levels that compare favorably with existing mental health chatbot deployments, with a mean SUS score of 76.55 that exceeds the industry average threshold of 68 and places the system in the good usability category. This result is above what primarily rule-based systems such as Woebot and Wysa have demonstrated in comparable student-facing evaluations, and it suggests that the combination of deep learning classification with large language model response generation produces a more natural and acceptable interaction than static scripted dialogue. The performance gap between

MindBridge and professionally mediated platforms such as BetterHelp is expected, as those platforms provide licensed human therapists rather than automated support.

The current system has one fundamental limitation in that the deterministic crisis detection module relies on a fixed keyword list and cannot detect indirect or metaphorical expressions of crisis that do not match predefined phrases. This gap cannot be fully resolved through better generation methods alone, as it requires richer contextual understanding of how students express distress across different cultural and linguistic backgrounds. Future work could address this through two approaches: expanding the crisis keyword corpus using data-driven methods drawn from student interaction logs and incorporating a secondary probabilistic crisis classifier trained specifically on indirect suicidal ideation expressions. The system's web-based deployment also currently operates in a single-user testing environment, and full multi-user deployment with concurrent session handling will be required to provide real-world evidence of the system's scalability and effectiveness in active student populations.

CONCLUSION

This project offers proof that it is possible to create a powerful and privacy-conscious AI-based system for mental health support, using only publicly available tools and datasets, within the limits of a university research project. MindBridge, by addressing both the technical and human sides of mental health care, is making a worthwhile contribution to the digital mental health tools that are becoming more and more popular.

One of the major successes of the system is its specialized deep learning model, which can successfully pinpoint emotional distress in student writing with great precision.

The crisis identification module establishes essential safety by ensuring that hazardous inputs are not only recognized but also lead to an instantaneous response. The system's conversational style makes it appear as a warm and compassionate friend rather than a cold, clinical diagnostic tool, and this stems from a deliberate choice to reduce the stigma that is often associated with seeking mental health help.

MindBridge is playing a major role in the global battle to deliver mental health support to young people in a more accessible way through its secure log-in, AI-facilitated emotional analysis, and empathetic response generation capabilities.

REFERENCES

Ahad, A. A., Sanchez-Gonzalez, M., & Junquera, P. (2023). Understanding and Addressing Mental Health Stigma Across Cultures for Improving Psychiatric Care: A Narrative Review. *Cureus*, (5). https://doi.org/10.7759/cureus.39549

Alsagri, H. S., & Ykhlef, M. (2020). Machine learning-based approach for depression detection in twitter using content and activity features. *IEICE Transactions on Information and Systems*, E103D(8), 1825–1832. https://doi.org/10.1587/transinf.2020EDP7023

Amanvermez, Y., Zhao, R., Cuijpers, P., de Wit, L. M., Ebert, D. D., Kessler, R. C., Bruffaerts, R., & Karyotaki, E. (2022). Effects of self-guided stress management interventions in college students: A systematic review and meta-analysis. *Internet Interventions*, 28. https://doi.org/10.1016/j.invent.2022.100503

Appleton, R., Williams, J., Juan, N. V. S., Needle, J. J., Schlief, M., Jordan, H., Rains, L. S., Goulding, L., Badhan, M., Roxburgh, E., Barnett, P., Spyridonidis, S., Tomaskova, M., Mo, J., Harju-Seppänen, J., Haime, Z., Casetta, C., Papamichail, A., Lloyd-Evans, B., … Johnson, S. (2021). Implementation, Adoption, and Perceptions of Telemental Health during the COVID-19 Pandemic: Systematic Review. *Journal of Medical Internet Research*, 23(12). https://doi.org/10.2196/31746

Bokolo, B. G., & Liu, Q. (2023). Deep Learning-Based Depression Detection from Social Media: Comparative Evaluation of ML and Transformer Techniques. *Electronics (Switzerland)*, 12(21). https://doi.org/10.3390/electronics12214396

Brooke, J. (1996). SUS-A quick and dirty usability scale. *Usability Evaluation in Industry*, 189–194.

Cruz-Gonzalez, P., He, A. W. J., Lam, E. P. P., Ng, I. M. C., Li, M. W., Hou, R., Chan, J. N. M., Sahni, Y., Vinas Guasch, N., Miller, T., Lau, B. W. M., & Sánchez Vidaña, D. I. (2025). Artificial intelligence in mental health care: A systematic review of diagnosis, monitoring, and intervention applications. *Psychological Medicine*, 55. https://doi.org/10.1017/S0033291724003295

Hoose, S., & Králiková, K. (2024). Artificial Intelligence in Mental Health Care: Management Implications, Ethical Challenges, and Policy Considerations. *Administrative Sciences*, 14(9). https://doi.org/10.3390/admsci14090214

Hua, Y., Siddals, S., Ma, Z., Galatzer-Levy, I., Xia, W., Hau, C., Na, H., Flathers, M., Linardon, J., Ayubcha, C., & Torous, J. (2025). Charting the evolution of artificial intelligence mental health chatbots from rule-based systems to large language models: a systematic review. *World Psychiatry*, 24(3), 383–394. https://doi.org/10.1002/wps.21352

Ji, S., Zhang, T., Ansari, L., Fu, J., Tiwari, P., & Cambria, E. (2021). MentalBERT: Publicly Available Pretrained Language Models for Mental Healthcare. *Proceedings of the 13th Language Resources and Evaluation Conference*, 7184–7190. https://aclanthology.org/2022.lrec-1.778

Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: state of the art, current trends and challenges. *Multimedia Tools and Applications*, 82(3), 3713–3744. https://doi.org/10.1007/s11042-022-13428-4

Lata, A., & Singh, S. K. (2025). AI in Healthcare: Revolutionizing Diagnosis, Treatment, and Patient Care Through Machine Learning. *Darpan International Research Analysis*, 13(1), 40–45. https://doi.org/10.36676/dira.v13.i1.162

Lattie, E. G., Cohen, K. A., Hersch, E., Williams, K. D. A., Kruzan, K. P., MacIver, C., Hermes, J., Maddi, K., Kwasny, M., & Mohr, D. C. (2022). Uptake and effectiveness of a self-guided mobile app platform for college student mental health. *Internet Interventions*, 27. https://doi.org/10.1016/j.invent.2021.100493

Moore, J., Grabb, D., Agnew, W., Klyman, K., Chancellor, S., Ong, D. C., & Haber, N. (2025). Expressing stigma and inappropriate responses prevents LLMs from safely replacing mental health providers. *ACM FAccT 2025 - Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency*, 599–627. https://doi.org/10.1145/3715275.3732039

Moulaei, K., Bahaadinbeigy, K., Mashoof, E., & Dinari, F. (2023). Design and development of a mobile-based self-care application for patients with depression and anxiety disorders. *BMC Medical Informatics and Decision Making*, 23(1). https://doi.org/10.1186/s12911-023-02308-y

Na, M., & Lee, J. (2024). Generative AI-Enabled Energy-Efficient Mobile Augmented Reality in Multi-Access Edge Computing. *Applied Sciences (Switzerland)*, 14(18). https://doi.org/10.3390/app14188419

Nyakhar, S., & Wang, H. (2025). Effectiveness of artificial intelligence chatbots on mental health & well-being in college students: a rapid systematic review. *Frontiers in Psychiatry*, 16. https://doi.org/10.3389/fpsyt.2025.1621768

Rashkin, H., Smith, E. M., Li, M., & Boureau, Y.-L. (2019). Towards Empathetic Open-domain Conversation Models: a New Benchmark and Dataset. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 5370–5381. https://doi.org/10.18653/v1/P19-1534

Vasim, K. A., Ashokbhai, P. K., Biswas, B., Soham, S., Patel, D., & Gurha, S. (2025). Mental Health Awareness and Stigma in the General Population: A Mixed-Methods Approach in Semi-Urban Areas. *Cureus*. https://doi.org/10.7759/cureus.100401

Wang, R. A. H., Smittenaar, P., Thomas, T., Kamal, Z., Kemp, H., & Sgaier, S. K. (2024). Geographical variation in perceptions, attitudes and barriers to mental health care-seeking across the UK: A cross-sectional study. *BMJ Open*, 14(3). https://doi.org/10.1136/bmjopen-2023-073731

Wani, C., McCann, L., Lennon, M., & Radu, C. (2024). Digital Mental Health Interventions for Adolescents in Low- and Middle-Income Countries: Scoping Review. *Journal of Medical Internet Research*, 26. https://doi.org/10.2196/51376

World Health Organization. (2023, June 8). Mental health: strengthening our response. *WHO News Room*. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response